Lab 3 - report, Michał Błaszczak [245047]

Task 1 (Grid search for simple exponential smoothing)

```
import numpy as np
import pandas as pd
from statsmodels.tsa.api import SimpleExpSmoothing, Holt
import matplotlib.pyplot as plt
```

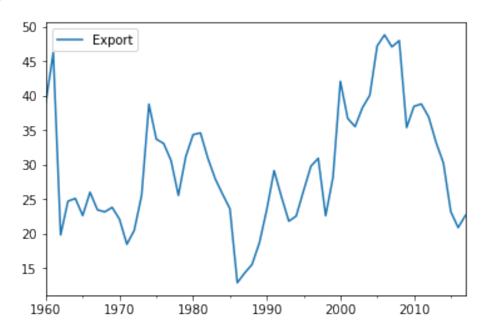
import data

```
df = pd.read_pickle('AlgerianExport.pkl')
df.head()
```

	Export
1960-12-31	39.043173
1961-12-31	46.244557
1962-12-31	19.793873
1963-12-31	24.684682
1964-12-31	25.084059

```
df.plot().legend()
```

```
<matplotlib.legend.Legend at 0x7f99da3b9df0>
```




```
len(df)
```

```
58
```

define SES function

```
def SES(df, alpha):
    SES_array = np.array([39.043173, ])
    for i in range(0, 57):
        value = alpha * df.iloc[i][0] + (1 - alpha) * SES_array[i]
        SES_array = np.append(SES_array, value)

    index = pd.date_range(start="1960", end="2018", freq="Y")
    SES_df = pd.DataFrame(SES_array, columns = ['Exports'])
    SES_df = SES_df.set_index(index)

    return mean_squared_error(df, SES_df)
```

determine alpha with the smallest MSE

```
alphas = np.arange(0.75, 1.00, 0.01)
for i in alphas:
    alpha = i
    MSE = SES(df=df, alpha=i)
    print('alpha:', round(i, 2), '   MSE:', round(MSE, 3))
```

```
alpha: 0.75    MSE: 34.636
alpha: 0.76    MSE: 34.587
alpha: 0.77    MSE: 34.544
alpha: 0.78    MSE: 34.506
alpha: 0.79    MSE: 34.475
alpha: 0.8    MSE: 34.45
alpha: 0.81    MSE: 34.43
alpha: 0.82    MSE: 34.416
alpha: 0.83    MSE: 34.408
alpha: 0.84    MSE: 34.406
alpha: 0.85    MSE: 34.409
alpha: 0.86    MSE: 34.417
alpha: 0.87    MSE: 34.432
alpha: 0.88    MSE: 34.451
alpha: 0.89    MSE: 34.476
alpha: 0.9    MSE: 34.507
alpha: 0.91    MSE: 34.543
alpha: 0.92    MSE: 34.584
alpha: 0.93    MSE: 34.631
alpha: 0.94    MSE: 34.684
alpha: 0.95    MSE: 34.742
alpha: 0.96    MSE: 34.805
alpha: 0.97    MSE: 34.874
alpha: 0.98    MSE: 34.949
alpha: 0.99    MSE: 35.029
```

```
#best result (smallest MSE) is for alpha = 0.84, where MSE: 34.406
```

fit and forecast data using library models

```
fit = SimpleExpSmoothing(df, initialization_method="estimated").fit()
a = fit.model.params["smoothing_level"]
fcast = fit.forecast(3).rename(r"$\alpha=%s$" % a)
MSE = mean_squared_error(df, fit.fittedvalues)
print('MSE:', round(MSE, 3))
```

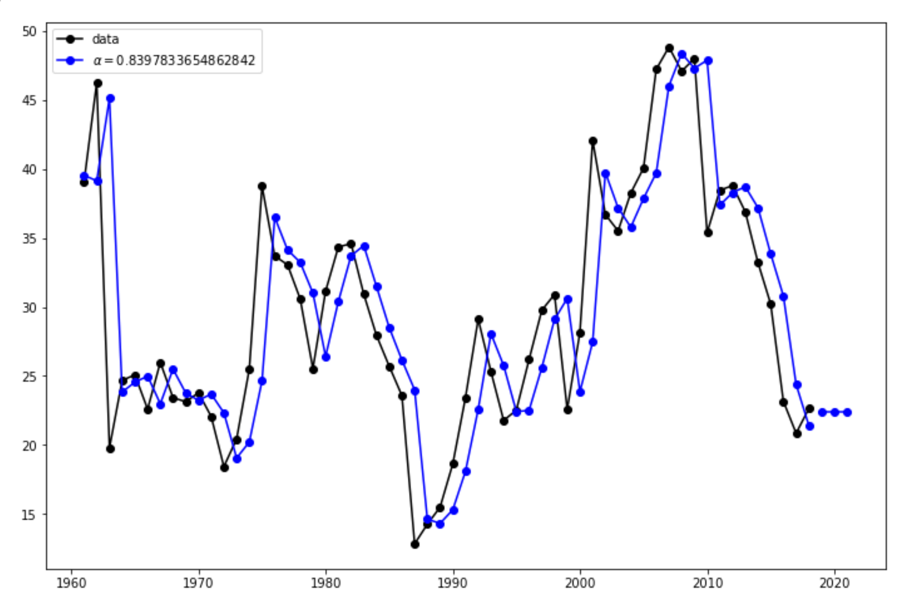
```
MSE: 34.401
```

plot results

```
plt.figure(figsize=(12,8))
(line0, ) = plt.plot(df, marker="o", color="black")
plt.plot(fit.fittedvalues, marker="o", color="blue")
(line1, ) = plt.plot(fcast, marker="o", color="blue")

plt.legend([line0, line1], ['data', fcast.name])
```

```
<matplotlib.legend.Legend at 0x7f9a0935b460>
```



Task 2 (Time series forecasting workflow)

read dataframe saved earlier using df.to_pickle('AlgerianExport.pkl')

```
df = pd.read_pickle('AlgerianExport.pkl')
```

```
df.head(5)
```

	Export
1960-12-31	39.043173
1961-12-31	46.244557
1962-12-31	19.793873
1963-12-31	24.684682
1964-12-31	25.084059

```
df.size
```

```
58
```

divide data into train and test

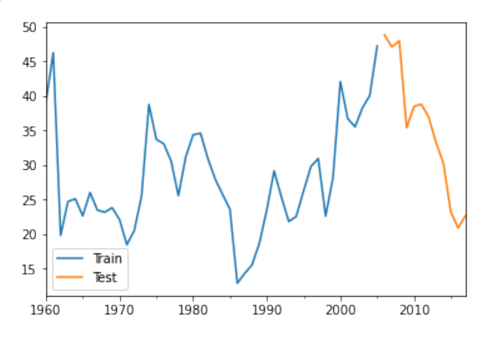
```
ncut=int(0.8*df.size) # 80% for training the rest is withheld for testing
ncut
```

```
46
```

```
train_data=df.iloc[:ncut]
test_data=df.iloc[ncut:]
```

```
ax=train_data.plot()
test_data.plot(ax=ax)
ax.legend(['Train','Test'])
```

```
<matplotlib.legend.Legend at 0x7f99da7de760>
```



fit the model

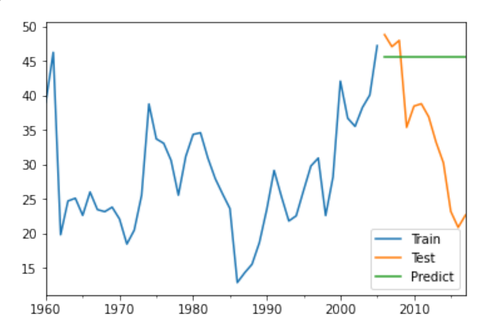
```
fitted_model=SimpleExpSmoothing(train_data,initialization_method='estimated').fit()
```

```
test_predictions=fitted_model.forecast(test_data.size).rename('SES forecast')
```

evaluate the model

```
ax=train_data.plot()
test_data.plot(ax=ax)
test_predictions.plot(ax=ax)
ax.legend(['Train','Test','Predict'])
```

```
<matplotlib.legend.Legend at 0x7f99e8cc1ee0>
```



evaluate metrics

```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import  mean_absolute_error,mean_absolute_percentage_error
```

MSE

```
mean_squared_error(test_data,test_predictions)
```

```
192.04697370873177
```

```
np.sum(np.square(np.subtract(test_data["Export"].values,test_predictions.values)))/test_data.size
```

```
192.04697370873177
```

MAE

```
mean_absolute_error(test_data,test_predictions)
```

```
11.439487998291211
```

MAPE

```
mean_absolute_percentage_error(test_data,test_predictions)
```

```
0.4216657162083754
```

```
np.sum(np.divide(np.abs(np.subtract(test_data["Export"].values,test_predictions.values)),test_data["Export"].values))/12
```

```
0.4216657162083754
```

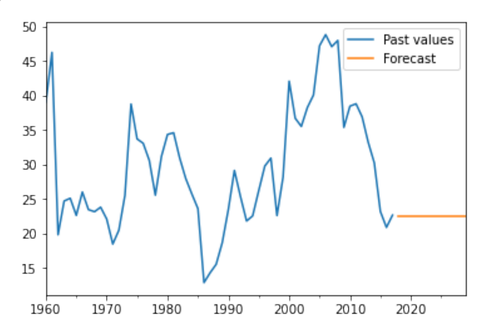
future forecasting

let us assume that the model presented above turned out to be the best; we train the final model using all available data points

```
# we use all available data
final_model=SimpleExpSmoothing(df,initialization_method='estimated').fit()
forecast=final_model.forecast(test_data.size).rename('forecast')
```

```
ax=df.plot()
forecast.plot(ax=ax)
ax.legend(['Past values','Forecast'])
```

```
<matplotlib.legend.Legend at 0x7f9a09441460>
```



Task 3 (Holt's method : double exponential smoothing)

read data

```
df = pd.read_csv('IBM.csv', index_col='Date', parse_dates=True)
df
```

Date	Open	High	Low	Close	Adj Close	Volume
1962-02-01	6.978967	7.087317	6.978967	7.068196	1.577107	674670
1962-02-02	7.068196	7.112811	7.036329	7.112811	1.587062	533460
1962-02-05	7.112811	7.112811	6.985341	7.023582	1.567153	329490
1962-02-06	7.023582	7.036329	6.998088	7.029955	1.568788	274575
1962-02-07	7.036329	7.074570	7.036329	7.036329	1.570211	266730
...	...	...	...	...	...	...
1965-12-23	8.022626	8.022626	7.950924	7.950924	1.781072	301248
1965-12-27	7.966858	8.038560	7.966858	7.966858	1.784643	364008
1965-12-28	7.966858	8.002709	7.919057	8.002709	1.792673	382836
1965-12-29	7.992750	7.992750	7.934990	7.934990	1.777503	320076
1965-12-30	7.934990	7.966858	7.934990	7.966858	1.784643	257316

985 rows × 6 columns

choose close prices only

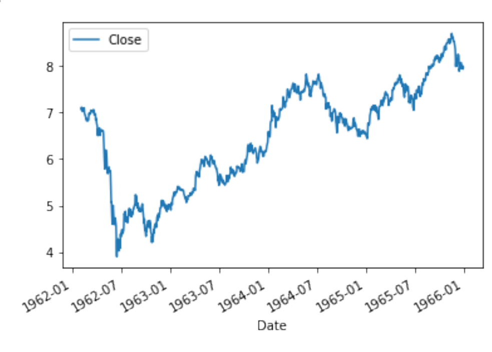
```
df = df['Close']
df
```

```
Date
1962-02-01    7.068196
1962-02-02    7.112811
1962-02-05    7.023582
1962-02-06    7.029955
1962-02-07    7.036329
                ...
1965-12-23    7.950924
1965-12-27    7.966858
1965-12-28    8.002709
1965-12-29    7.934990
1965-12-30    7.966858
Name: Close, Length: 985, dtype: float64
```

plot close price data

```
df.plot().legend()
```

```
<matplotlib.legend.Legend at 0x7f99fbe58220>
```



set the frequency of the time series to business days

```
df = df.asfreq('b')
df.index
```

```
DatetimeIndex(['1962-02-01', '1962-02-02', '1962-02-05', '1962-02-06',
               '1962-02-07', '1962-02-08', '1962-02-09', '1962-02-12',
               '1962-02-13', '1962-02-14',
               ...
               '1965-12-17', '1965-12-20', '1965-12-21', '1965-12-22',
               '1965-12-23', '1965-12-24', '1965-12-27', '1965-12-28',
               '1965-12-29', '1965-12-30'],
              dtype='datetime64[ns]', name='Date', length=1021, freq='B')
```

use forward fill to remove nans

```
df = df.ffill(axis=0)
df
```

```
Date
1962-02-01    7.068196
1962-02-02    7.112811
1962-02-05    7.023582
1962-02-06    7.029955
1962-02-07    7.036329
                ...
1965-12-24    7.950924
1965-12-27    7.966858
1965-12-28    8.002709
1965-12-29    7.934990
1965-12-30    7.966858
Freq: B, Name: Close, Length: 1021, dtype: float64
```

select part of the time series for which the long-term linear trend is apparent - at this point I will stick to Friday's [18 March] lecture notes

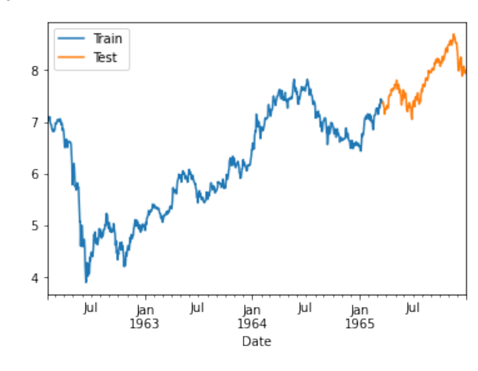
```
ncut=int(0.8*len(df))
ncut
```

```
816
```

```
train_data = df.iloc[:ncut]
test_data = df.iloc[ncut:]
```

```
ax = train_data.plot()
test_data.plot(ax=ax)
ax.legend(['Train', 'Test'])
```

```
<matplotlib.legend.Legend at 0x7f99fc00ce80>
```



fit and forecast Simple Exponential Smoothing model

```
fitSES = SimpleExpSmoothing(train_data).fit()
fcastSES = fitSES.forecast(len(test_data)).rename('SES predict')
```

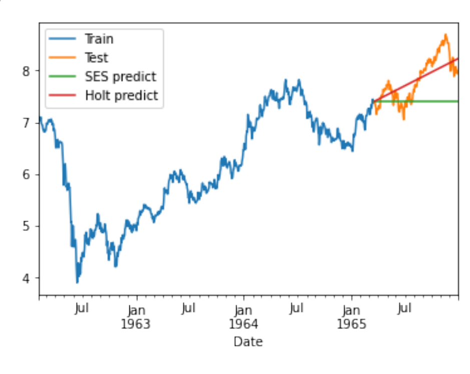
fit and forecast Holt model

```
fitHolt = Holt(train_data, exponential=False).fit()
fcastHolt = fitHolt.forecast(len(test_data)).rename('Holt predict')
```

compare SES and Holt

```
ax = train_data.plot()
test_data.plot(ax=ax)
fcastSES.plot(ax=ax)
fcastHolt.plot(ax=ax)
ax.legend(['Train', 'Test', 'SES predict', 'Holt predict'])
```

```
<matplotlib.legend.Legend at 0x7f99fc03ddf0>
```




```
print("Mean Absolute Percentage Errors:")
SES_mape = mean_absolute_percentage_error(test_data, fcastSES)*100
print("  ", SES_mape, "%")
Holt_mape = mean_absolute_percentage_error(test_data, fcastHolt)*100
print("  ", Holt_mape, "%")
```

```
Mean Absolute Percentage Errors:
   5.7993546222452865 %
   2.804980221395473 %
```